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Technical note

Application of time-varying analysis to diagnostic needle electromyography

Geoffrey L. Sheean*

University of California, San Diego, Neuromuscular Division, 402 Dickinson Street, Suite 190, San Diego, CA 92103-8465, USA

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ABSTRACT

Quantification in clinical, diagnostic electromyography (EMG) currently includes motor unit action potential (MUAP) analysis and interference pattern analysis. Early efforts to examine the frequency/power spectra of the interference pattern showed modest value but the technique was not developed further. This paper re-examines spectral analysis, extending it into the time-varying domain, which has never been studied in diagnostic needle EMG. Time–frequency and time-scale analysis employing wavelet and non-wavelet techniques were applied to short trains of MUAPs. The results show that time-varying analysis produces clear visual representations of the energy content of individual MUAPs within an interference pattern. The time frequency representations allow easy, qualitative distinction between normal and neurogenic MUAPs. Furthermore, the quantified MUAP energy correlates well with the current morphological standard and the quantification process is substantially faster. Time-varying analysis links classical power spectral analysis in the realm of interference patterns with quantitative MUAP analysis. In addition to morphological classification, MUAPs might also be classified by energy content, which more closely reflects the physical and physiological consequences of neuromuscular pathology on the motor unit.

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1. Introduction

In clinical practice, electromyographic (EMG) analysis is usually subjective and performed in real time as the signal is being acquired by observing an oscilloscope-style display, usually on a computer screen. Although modern EMG machines have the ability to record the EMG signals, this is rarely done and even if the recordings are reviewed afterwards, quantification is the exception and the analysis usually remains subjective and visual. The subjectivity and real-time analysis makes learning the technique of diagnostic EMG very difficult and the acquisition of the signal and its interpretation is highly operator-dependent. Thus, there has been long-standing interest in quantification since the early days of clinical EMG.

Quantification of diagnostic electromyographic (EMG) signals currently involves either morphological analysis of individual motor unit action potentials (MUAP), or analysis of the interference pattern (IP) by the turns-amplitude method [1] and the fields are quite separate. Early studies of the interference pattern power spectrum showed some promise but did not garner much clinical or research traction. For example, neurogenic MUAPs were found to have a large amount of low frequency power and myopathic MUAPs had more high frequency power [1]. Clinically, power spectral analysis seemed to have modest discriminatory value for neurogenic muscles [2] and in myopathy [3].

EMG recordings from the skin surface (surface EMG) have been used extensively in studies of kinesiology and related fields [4]. However, surface EMG does not reveal sufficient fine detail about the morphology of the MUAP to be adequate for clinical testing. Using a needle inserted into the muscle allows for selective searching and focusing on specific MUAPs, which can be readily distinguished from each other (c.f. surface EMG), and for analysis of MUAPs in the deeper parts of the muscle, which are not accessible by surface EMG.

The MUAP size reflects the size of a motor unit, especially the number of muscle fibers in the motor unit [5]. In myopathic conditions, the motor unit loses muscle fibers, becomes weaker, and its MUAP becomes smaller. In neurogenic conditions, when a motor unit loses its innervation, adjacent nerves branch out to reinnervate some of the muscle fibers in the denervated motor unit, thereby enlarging their own motor unit size and territory. The resulting MUAPs are therefore larger. Hence, one of the main questions in clinical electromyography is, are the motor units in this muscle normal, or abnormally large (neurogenic) or small (myopathic)? When observing MUAPs, either in real-time or in static images, the

Abbreviations: CWD, Choi–Williams distribution; CWT, continuous wavelet transformation; EEG, electroencephalogram; EKG, electrocardiogram; EMG, electromyography; FFT, fast Fourier transform; MUAP, motor unit action potential; SAPW, smoothed affine pseudo Wigner distribution; SI, size index; TFR, time–frequency representation; TSR, time-scale representation.

* Tel.: +1 619 543 5300; fax: +1 619 543 5793.
E-mail address: gsheean@ucsd.edu

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amplitude is the easiest parameter to gauge, but this is not always the best measure of the overall size of the MUAP, especially for neurogenic MUAPs. Sometimes, high-amplitude MUAPs are quite thin and not neurogenic. This led to the development of MUAP thickness and the Size Index [6], which takes into account the area and the amplitude of the MUAP, but this too is difficult to gauge subjectively. Myopathic MUAPs are somewhat easier to identify, since they are usually both low in amplitude and area.

Since we know that the size of a MUAP reflects the size and force generating capacity of a motor unit [7], it seems intuitive that studying the energy content of MUAPs could yield useful clinical information. Advances in digital signal processing and in computing power prompted this re-examination of the potential applicability of spectral analysis of diagnostic EMG. Time-varying displays of EMG energy might allow better visual identification of abnormal MUAPs, especially large, neurogenic MUAPs, and confirmation of these detected outliers through quantification of MUAP energy. This paper presents the results of some preliminary analysis with these techniques to show their potential value in clinical electromyography. However, there is much greater potential beyond subjective visual analysis, in regard to EMG quantification.

2. Methods

This section will briefly address the problems of the first technique used in frequency analysis of needle EMG, followed by a description of time-varying signal analysis and its two main subtypes, and of energy quantification, by way of background. The final segments describe the specific methods used in this study (beginning at 2.6).

2.1. Power spectral analysis

Traditional spectral analysis of EMG consists of a fast Fourier transformation (FFT) of the EMG signal. The output displays the range and amplitude of the component frequencies but does not say anything of the distribution of these frequencies over time. Graphic displays of the FFT shows the energy distribution of the signal but also without localization in time (Fig. 1). Since abnormal MUAPs might be mixed in among many normal MUAPs and may be few in number, traditional spectral analysis of the EMG would be poorly sensitive in detecting abnormal MUAPs. The need for time information in addition to frequency makes the FFT and related techniques unsuitable for analysis of EMG signals, which are non-stationary. In non-stationary signals, the frequency spectrum of the signal changes over time. Analysis of non-stationary signals has progressed substantially since EMG power spectra were last studied.

2.2. Time-varying analysis

The need for both time and frequency based signal analysis led to an elegantly simple solution of breaking up the signal into segments and performing a FFT on each segment, a technique called short-time FFT. However, technical limitations and problems associated with its spectrogram representation prompted development of a new class of techniques, time-varying analysis, which is better able to display the energy distribution of a non-stationary signal according to both time and frequency.

There are two types of time-varying energy representations, time–frequency (TFR) and time-scale (TSR) representations. Both display how a signal changes frequency and energy content over time but they differ mathematically. In TFR, time and frequency shift similarly or in-step when the spectrogram is formed (covariance). In TSR, time shifts covariantly with scale changes. Frequency is comparable to scale and the equivalent of the spectrogram is the

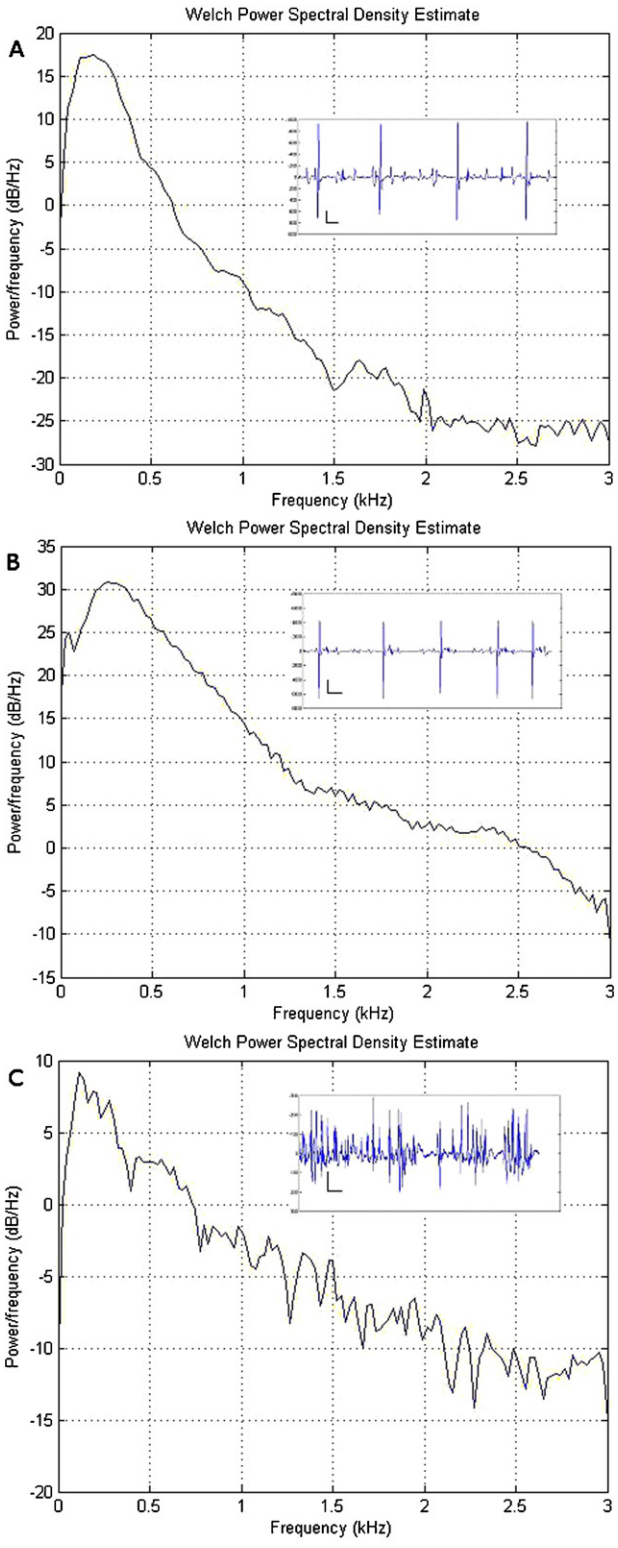

Fig. 1. The power spectral densities (PSD) of normal (A), neurogenic (B), and myopathic (C) interference patterns (embedded). There are small differences in scale and more subtle differences in shape. For example, the neurogenic PSD has more power in the lower frequency ranges than the normal IP, and the myopathic IP has more complexity with a less smooth outline. For the embedded EMG patterns, the scale markers show a time-base of 20 ms and amplitude in μV of 500 (A), 2000 (B), and 200 (C).

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scalogram. Time–frequency analysis has been used extensively on surface EMG, for example to study fatigue [4], but has never been applied to diagnostic needle EMG. The details follow and although the mathematical formulae are included, the reader can skip them readily without compromising understanding.

2.3. Time–frequency analysis

The basic TFR of a signal $x(t)$ is the Wigner–Ville distribution (WVD),

$$W_x(t,f) = 2\int_{-\infty}^{+\infty} x(t+\tau)x*(t-\tau)e^{4\pi\tau i}d\tau, \quad (1)$$

which has several desirable properties relevant to EMG signal analysis. In particular, it allows display of the energy density of a signal in terms of frequency and time simultaneously.

Unfortunately, the quadratic nature of the WVD necessarily introduces interference terms, caused by interaction between points on the time–frequency plane. These appear as artefacts and visually degrade the representation. Because the interference terms oscillate in both the time and frequency directions, they can be reduced by smoothing. Smoothing involves convolving the WVD with a smoothing kernel in time or frequency or both. Smoothing kernels fall into two main classes, the Cohen class and the affine class, and some are in both. Cohen class TFRs are time–frequency representations whereas affine class TFRs are time-scale representations. The amount of smoothing in the time or frequency domains can be adjusted separably (the preferred engineering term) or conjointly depending on the smoothing kernel. The downside to smoothing is loss of resolution in whichever domain or domains it is undertaken (i.e. frequency or time, or both).

The Cohen class TFR smoothing kernel $\varphi(t,f)$ is convolved with the WVD to produce,

$$C_x(t,f) = \int_\tau\int_\nu \Psi(\tau,\nu)\Lambda_x(\tau,\nu)e^{i2\pi(t\upsilon-f\tau)}d\tau\ d\nu, \quad (2)$$

where $\Psi(\tau,\upsilon)$ is the Fourier transform of the smoothing function $\varphi(t,f)$ and $\Lambda_x(\tau,\upsilon)$ is the ambiguity function of $x(t)$, which is also the Fourier transform of the WVD. Thus, smoothing can be performed separably in the time and frequency domains. The Choi–Williams distribution (CWD) is a type of Wigner–Ville based reduced interference distribution that smoothes in time and frequency conjointly. The Choi–Williams kernel is given by,

$$\Psi_{CWD}(\tau,\nu) = e^{-(2\pi\tau\nu)^2/\sigma}, \quad (3)$$

where σ is a positive parameter, which controls both τ and υ, with a larger σ providing less smoothing. Advantages of the this distribution are that it tends to have the least interference and the marginal properties are preserved, which allows for an energy time–frequency distribution (see Section 2.5).

It is usual to display the results of a TFR by the spectrogram, which is the squared modulus of the TFR, thus

$$S_x(t,f) = |TFR_x(t,f)|^2. \quad (4)$$

2.4. Time-scale analysis

Time-scale representations (TSR) include pure wavelet transformations and affine time–frequency representations. Wavelet-based analysis has been performed extensively on surface EMG of limbs for kinesiology purposes [4], as well as on EEG [8], EKG [9], and uterine surface EMG [10]. Wavelet methods have also been applied to needle EMG for classification of decomposed MUAPs [11], and for MUAP analysis through wavelet decomposition [12], but neither of these papers employed time-varying representations.

2.4.1. Wavelet analysis

Wavelets are small, simple waves (hence, 'wavelets') based on a 'mother' wavelet, which can be changed in size to match an area of the signal closely, while retaining the same overall shape. When high frequency areas are encountered, they shrink. When low frequency areas are encountered, they stretch. The amount of stretching or shrinking occurs on a fixed set of scales, much like notes on a musical scale, so that the scales can be thought of as a band of frequencies. However, scales are the inverse of frequency – high frequency means lower scale – if the base (mother) wavelet is well centered around zero. These properties make wavelets ideally suited for analysis of non-stationary signals, such as EMG.

The continuous wavelet transformation (CWT) of a signal x is given by the following.

$$Tx(t,a;\Psi) = \int_{-\infty}^{+\infty} x(s)\Psi_{t,a}(s)ds, \quad (5)$$

where $\Psi_{t,a}(s) = |a|^{-1/2}\Psi(s-(t/a))$. The variable a is the scale factor. By analogy to TFR, CWT is covariant in translation by time and scale and the energy time-scale distribution is the scalogram (the squared modulus of the CWT). However, the CWT and scalogram still suffer from the same time–frequency resolution tradeoff of the TFR.

2.4.2. Affine time–frequency representation

In addition to being time–frequency covariant, the WVD is also time-scale covariant or, more formally, has the desirable property of covariance by translation in both time and dilation. As such, the WVD belongs to the *affine* class of TFRs. This presents a way to improve the time–frequency resolution of the wavelet scalogram by using a covariant time-scale smoothing function, such as the *smoothed affine pseudo* Wigner distribution (SAPW). The smoothing kernel for this function is given by,

$$\Psi_{SAPW} = h\left(\frac{\tau}{a}\right)g\left(\frac{(s-t)}{a}\right), \quad (6)$$

where $g(t)$ and $h(t)$ are the time and frequency smoothing windows, respectively, to be applied as in Eq. (2). Essentially, this means that the signal is pre-processed with CWT before the TFR analysis.

2.5. Energy quantification

Time–frequency representations have what are called marginal distributions, which allow calculation of the energy content of a signal by time or frequency. The integral of the TFR with respect to time is the frequency marginal, which is the energy spectral density, so that

$$m_t(f) = \int_{-\infty}^{+\infty} TFR(t,f)dt = |X(f)|^2. \quad (7)$$

This results in a time–frequency plot, from which the energy level of each MUAP firing in an interference pattern or of each decomposed MUAP can be obtained.

2.6. Data acquisition

The EMG lab at the University of California, San Diego routinely records concentric needle EMG for post-test review and for teaching. The XCalibur Lite® (Nuance, Carlsbad, CA, USA) EMG machine is used, with bandpass set at 30 Hz–10 kHz and 60 Hz notch filter on. Sampling frequency was found to be 6 kHz rather than the advertised 60 kHz. This could have caused aliasing problems, based on the Nyquist frequency, but analysis of the EMG signal indicates little power over 3 kHz (not shown). The study was classified as exempt from permission by the UCSD Institutional Review Board

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because no patient identifiers are displayed and only archived data obtained during routine clinical testing has been used.

2.7. Data analysis

Analysis of the EMG signal was performed in Matlab R2010b©(Mathworks, Inc., Natick, MA, USA), with the signal processing toolbox. Time–frequency analysis was undertaken using the Choi–Williams formulation of the Wigner–Ville distribution in the v. 0.2 from Rice University [13], after exploring numerous TFR alternatives. Time-scale analysis (TSR) was performed in two ways, one a wavelet-based method, the *smoothed affine pseudo* Wigner distribution (SAPW), and the other a purely wavelet method, continuous wavelet transformation (CWT). Both analyses were performed in Fraclab [14]. The SAPW was chosen because of the clarity of its EMG signal scalogram and its computational speed. Selection of the wavelet was based on two principles: (1) it should resemble the MUAP as closely as possible in shape, and (2) it should be real, with no imaginary component, because the EMG signal is real. Trial and error showed that the Mexican Hat wavelet gave the best results for both the SAPW and the CWT. The wavelet name is derived from its shape and is a smooth, symmetrical triphasic waveform similar to some MUAPs. For both, 256 scales were used.

2.8. Direct MUAP quantification

Individual MUAPs were decomposed (extracted) from an interference pattern using EMGLab [15] and the energy of each was obtained from the frequency marginal of the CWD (Eq. (7)). The Size Index of the MUAPs was calculated from the formula, SI = 2log10[amplitude] + (area/amplitude) [6].

2.9. MUAP energy quantification from the interference pattern

As mentioned, the frequency marginal of the CWD contains the energy distribution of the signal over time. Instead of decomposing individual MUAPs from the interference pattern, the CWD could be applied to the interference pattern and the energy of a desired MUAP firing can be measured from that.

3. Results

3.1. Comparison of displays

The mixed EMG signals of normal and large MUAPs are shown together with their respective spectrograms and scalograms in Fig. 2. Each MUAP can be seen to have a corresponding image in the spectrogram or scalogram, except for the small normal MUAPs, which are very faint or invisible. The images representing the larger MUAPs within each of the scalograms (SAPW and CWT) are self-similar and firing semi-regularly, thereby establishing that they are the same MUAP. Small variations in appearance are caused by overlap with smaller MUAPs. Faint images of the smaller MUAPs in the normal and neurogenic trains remain in the CWT, compared with the SAPW.

3.2. Calibration of displays with reference signals

Fig. 2 is a quite obvious example of MUAP energy differences, provided for the purposes of illustration. Although the colourmap would provide some guide to the energy content of the MUAP representation, in a scalogram of an EMG signal with a modest mixture of MUAP types it might be very difficult to determine if any are pathological. One solution is to calibrate by inserting reference MUAPs into the signal. A more real-life EMG example is given in Fig. 3. Note the presence of a repetitively firing MUAP

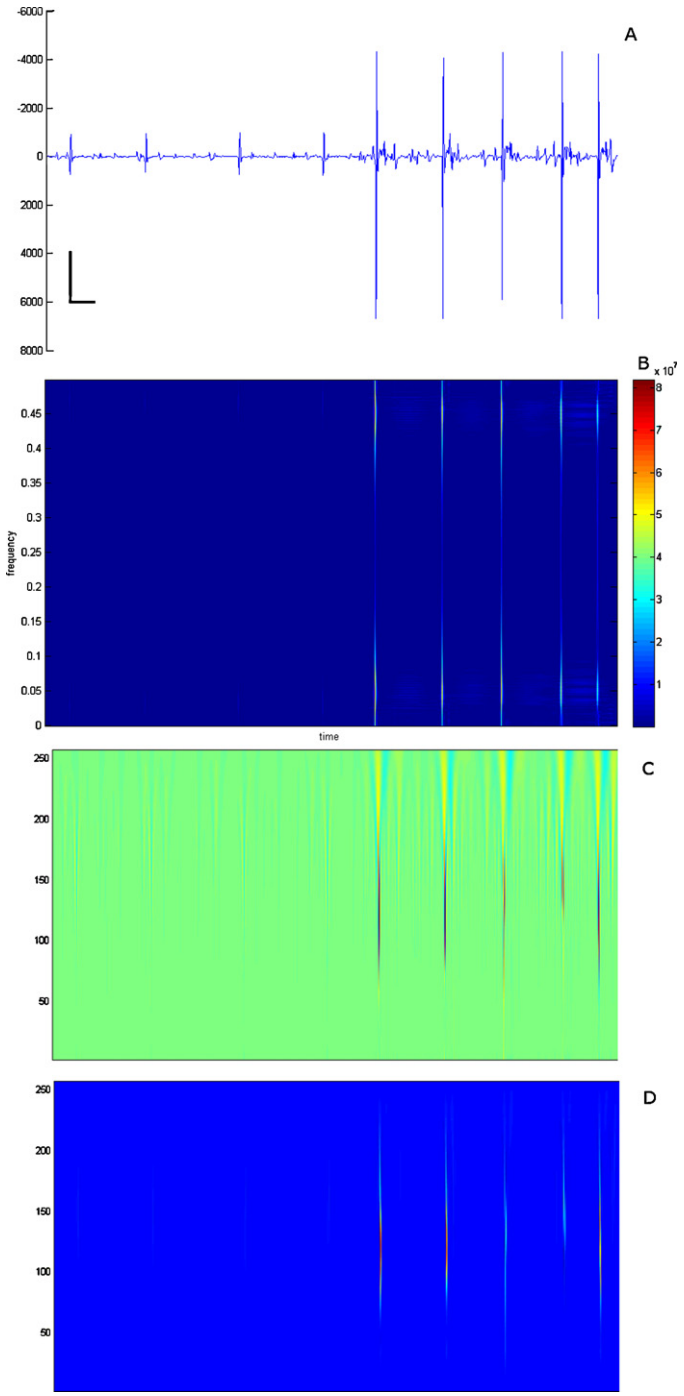

Fig. 2. (A). The normal-neurogenic EMG signal with calibration marker of 20 ms and 2000 μV. The first half of the signal is normal EMG, followed by neurogenic EMG. (B). The Choi–Williams (CWD) spectrogram of time vs. normalized frequency (0–0.5), representing 0–6 kHz. (C). The CWT scalogram, *Y*-axis scale 0-256. (D). The SAPW scalogram, which has a colouration chosen to differentiate it from the CWT. The *Y*-axis is scale from 0 to 256. Representations of the normal MUAPs are invisible or very faint and are really only visible in the CWT. Note the interference in the CWD appearing as faint smudges between the MUAP representations.

of clearly higher amplitude (double asterisk) than the others and another (single asterisk) that is just a little larger than the larger of the reference potentials. As expected, the SAPW shows that larger amplitude MUAP** has more energy than the largest reference MUAP and is in the same scale/frequency range. In contrast, the other MUAP* seems to have considerably more energy and has strong high scale/low frequency components, typical of neurogenic

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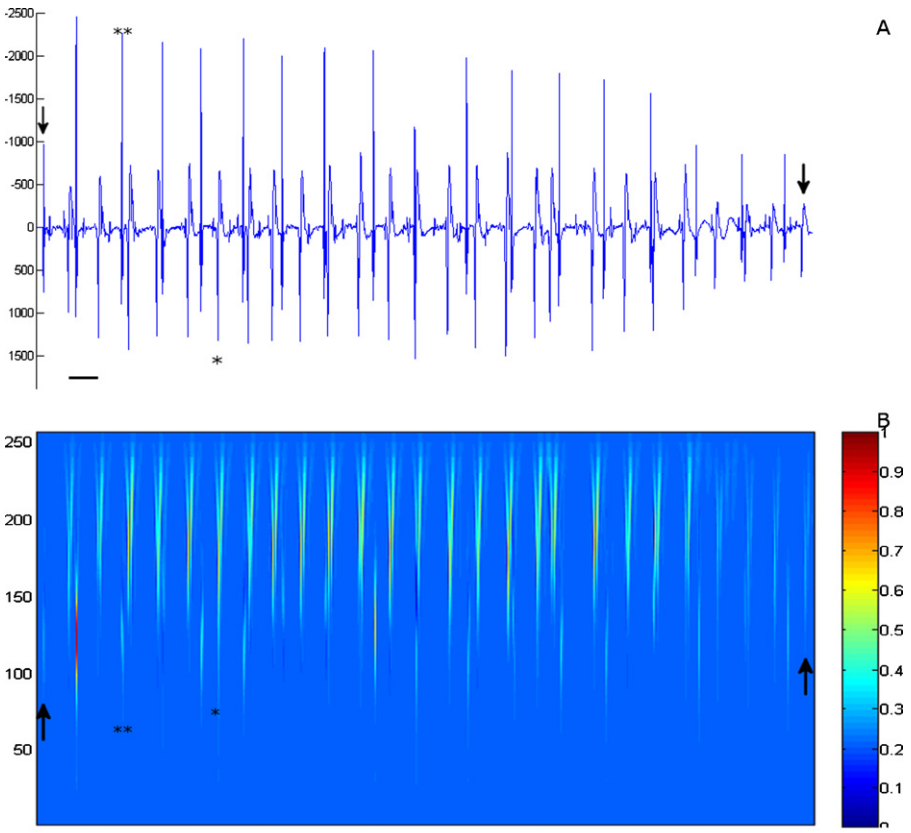

Fig. 3. (A) A real EMG interference pattern from biceps, calibration marker 100 ms, amplitude is in μV. Reference MUAPs have been inserted (arrows) at the beginning (SI = 1.9) and end (SI = 1.2) of the train. There is a repetitively firing MUAP that is clearly larger in amplitude (double asterisk) than the others, dominating the display, but there is another (asterisk) that is similar in amplitude to the larger reference MUAP at the beginning. (B) The SAPW representation with the 2 reference potentials also indicated by arrows. Note the simplification afforded by the TSR and that it is easy to determine that the largest amplitude MUAP** in the train contains more energy than the larger reference MUAP, although at a similar scale/frequency. In contrast, the more borderline MUAP* seems to be of much higher energy and is represented at a higher scale/lower frequencies than the other MUAPs: it is now the dominant feature of the display. The *Y*-axis is scale from 0 to 256. Only the SAPW is shown, for simplicity.

MUAPs [1]. Note that in the presence of the reference MUAPs most of the other MUAPs are faint or barely visible indicating that they are normal. Thus, this type of representation with reference MUAPs provides a form of filtering, allowing the observer to concentrate on high energy MUAPs. It also shows that MUAP amplitude is a poor reflection of its energy content.

Therefore, Fig. 3 is an example of the ability of time-varying analysis to display an EMG signal in time, energy, and frequency simultaneously. The clinical interpretation of Fig. 3 is that there are 2 high-energy MUAPs, one with strong medium-frequency components, and another with strong low-frequency components (neurogenic) among otherwise normal-energy MUAPs. Viewing the raw EMG signal vertically aligned with its scalogram provides a simultaneous energy and frequency interpretation of the signal.

3.3. Direct MUAP energy quantification

The energy of the decomposed MUAPs ($n = 16$) from another interference pattern (not shown) was plotted against the Size Index, revealing an exponential relationship between the two (Fig. 4A). To test this relationship further, a larger sample of simulated MUAPs ($n = 56$) was obtained for analysis from an EMG Simulator program [16] and the results for MUAP energy and Size Index are shown in Fig. 4B, again displaying a strong exponential correlation. Fig. 4 also shows that small MUAPs can have a negative Size Index. The energy analysis for each MUAP took less than 3 s whereas the time to calculate the Size Index was about 1–2 min (Intel Quad Core i7 975 3.33 GHz, 12 GB RAM, Windows 7 64-bit).

3.4. MUAP energy quantification from the interference pattern

The frequency marginal distribution of the Choi–Williams representation of the EMG signal in Fig. 3 is displayed in Fig. 5. Each MUAP firing is represented by a peak and the energy of each can be easily obtained from the area of the peak (examples adjacent to the peaks). This allows a quick quantification of MUAP energy directly from the interference pattern, without the need for time-consuming decomposition. Note that the 2 high energy MUAPs (a and b) have similar total energy and about 3 times the energy of the largest reference MUAP (d).

4. Discussion

Time-varying analysis by spectrogram or scalogram provides another way of visualizing an EMG signal to supplement routine subjective analysis. Instead of simple waveforms, the MUAPs are displayed as pulses of energy within the EMG signal.

Two types of representation were examined, TFR and TSR. Overall, TSR is preferred over TFR for a time-varying energy representation of EMG because of the clarity of the images: the CWD can be degraded by interference terms (only seen close-up and in colour in Fig. 2B). Also, the TSRs are computed much more quickly than the TFR. The SAPW displays are visually appeal-

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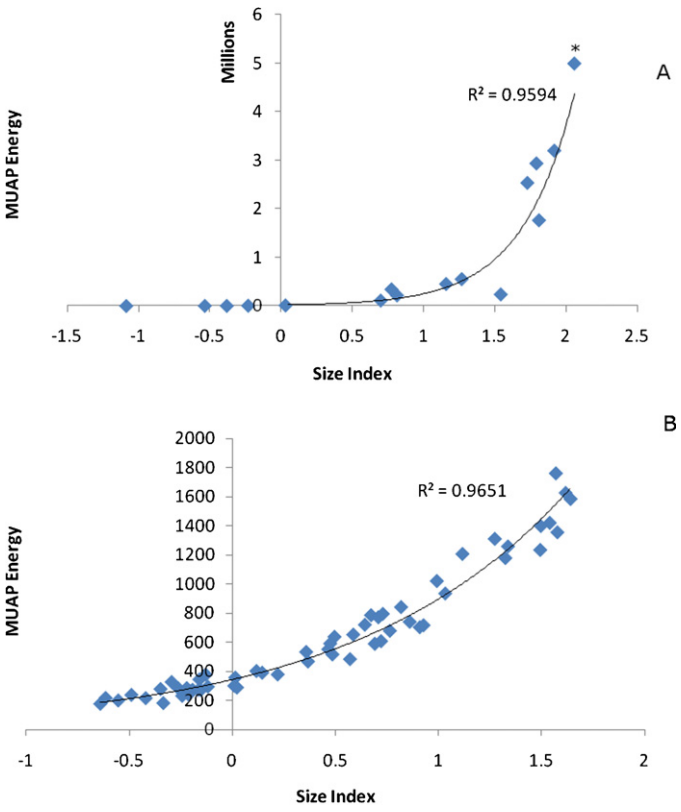

Fig. 4. (A) A plot of the Size Index of the MUAPs ($n = 16$) decomposed from another interference pattern against MUAP Energy, showing a strong, exponential correlation ($p < 0.01$). The data point corresponding to the larger reference MUAP is indicated by an asterisk, which appears as an outlier at the end of the series. Note that some small MUAPs have a negative Size Index. (B) A plot of MUAP energy against Size Index for simulated MUAPs ($n = 56$) also showing a very strong, exponential correlation ($p < 1e{-}28$). Note the differences of energy values between the real and simulated MUAPs, for technical reasons.

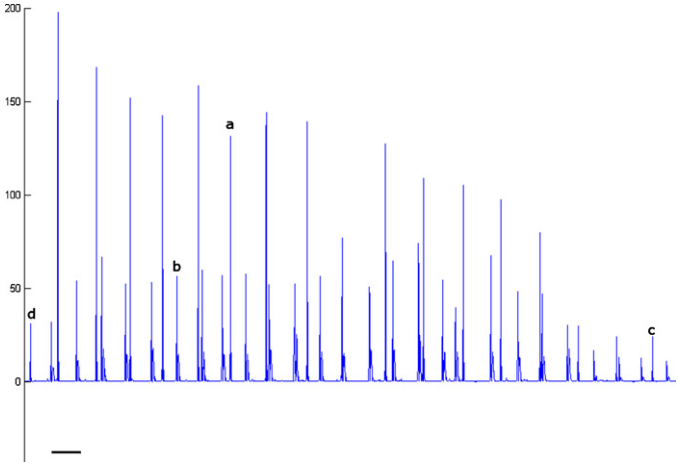

Fig. 5. The frequency marginal distribution against time (time–energy distribution) of the CWD of the EMG signal in Fig. 3. The energies of several peaks representing MUAP firings are indicated: $a = 1029.8$, $b = 1035.2$, $c = 210.2$, $d = 326.8$. Note that d = the largest reference MUAP and a and b are the high-energy MUAPs from Fig. 3: both have about 3 times as much energy as the largest reference MUAP. The time base is 100 ms, amplitude in units.

ing and the higher-energy waveforms in the signal are very clear while lower energy MUAPs are very faint: small MUAPs are more easily seen in the CWT display because of the chosen colouration.

4.1. Significance of the scalogram

The scalograms are not just a colourful way of displaying MUAPs: the colour and brightness of the signal on the TFR/TSR representation corresponds to the energy content of the MUAP, and directly answers one of the basic questions being asked in clinical EMG – is the MUAP (and its corresponding motor unit) normal, small, or enlarged? – and displays the answer in a clear, colour image. At present, the visualization seems better suited for identifying large MUAPs (neurogenic) than small MUAPs (myopathic), but this is by far the more common question in clinical EMG studies. Furthermore, it is possible to determine in which frequency or scale range the energy is concentrated.

4.2. Comparison with standard methods

An advantage of this type of display of the EMG signal over the traditional oscilloscope-style display is that large MUAPs stand out quite clearly, especially when the signal is calibrated by the addition of reference MUAPs, which apply a form of filtering. Thus, there is less distraction from low-energy MUAPs and potentially from high-amplitude, thin MUAPs that do not have high energy. As mentioned, time-varying analysis, especially the scalogram, also provides spatial separation of MUAPs based on their frequency content. For clinicians, re-presentation of the raw EMG data as a time–frequency display, with calibration from reference potentials, would help them determine whether large (neurogenic) MUAPs are present, without the need to perform complicated quantitative analysis. This method, therefore, simplifies qualitative EMG interpretation.

However, the potential clinical application is not only as an alternative way to display EMG signals as energy pulses, but that the energy content of EMG signals can be quantified and displayed as a function of time. The analysis of MUAP energy shows an excellent correlation with the standard MUAP measure, the Size Index, but requires no time-consuming measurements of amplitude, duration, and area, and no calculation of a formula to yield a result (the Size Index), which has no true physical meaning, especially considering that small MUAPs have negatively valued results (see Fig. 4). Furthermore, it is possible to obtain an MUAP energy measurement from the interference pattern, without decomposition to individual MUAPs, from frequency marginal of the CWD of the IP. Energy-based quantification of EMG is intuitively appealing, given that the purpose of motor units is to generate muscle force. Thus, unlike the Size Index, the energy content of a MUAP is a direct measure of the force generating capacity of the motor unit and by inference a direct reflection of the physiological and pathological consequences of neuromuscular disease on the motor unit. A morphological description of the MUAP describes the shape and not the content of the signal, much like expecting a person with well-defined muscles to be strong–morphology is an outline, energy is content.

5. Conclusion

This paper is intended to update spectral analysis of clinical, diagnostic needle EMG signals through introduction of time-varying analysis. This simplifies qualitative interpretation of diagnostic EMG and opens up an entirely new field of clinical EMG analysis based upon energy, including quantification of individual MUAP and IP energy. Applying the methods directly to interference patterns, but examining the energy of individual MUAPs qualitatively and quantitatively, provides a link between traditional interference pattern analysis and quantitative MUAP analysis, which had been previously quite separate. The notion of

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describing diagnostic EMG as an energy signal, rather than a purely morphological signal, represents a dramatic paradigm shift in EMG analysis. The methods presented here will serve as the basis of future research, which will include further exploration of the quantification of energy for MUAP and interference pattern analysis, and the development of techniques to perform automated, and possibly real-time analysis.

Conflict of interest

None.

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